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Waiting on You: A Study of Tipped Minimum Wages' Effects on Job Tenure Among White Restaurant Servers

John Henry Sienkiewicz
Loyola University Chicago

LOYOLA UNIVERSITY CHICAGO

WAITING ON YOU:

A STUDY OF TIPPED MINIMUM WAGES' EFFECTS ON JOB TENURE

AMONG WHITE RESTAURANT SERVERS

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JOHN H. SIENKIEWICZ

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Introduction

According to the United States Bureau of Labor Statistics, service jobs comprised 79.9% of all types of work in America in 2012 (United States Bureau of Labor Statistics 2014). The days of America as an industrial powerhouse passed long ago, and the service industry now dominates the economy. Concurrent with the rise of service occupations in the American economy and the loosening of outdated labor market regulations since the 1970's has been a rise in "precarious work;" work that is low wage, unstable, lacking benefits and subject to poor working conditions. As researcher Janice Fine (2015) writes, "Meanwhile, precarious employment, sub-standard conditions and marginalization have become widespread features of the labour market" (Fine 2015: 15). Additionally, Janice Fine and Ruth Milkman have shown that immigrants and minorities are much more likely to be employed in precarious work than native born and white people, and that certain industries have much higher concentrations of precarious work than others—industries such as retail, care work and hospitality.

Moreover, these scholars emphasize that legal, political, and policy decisions have created precarious work and that different decisions can significantly improve working conditions for the people at the bottom of the American labor market. For instance, they show how better enforcement of existing labor laws, updated laws for the “gig economy,” support for unions and worker’s centers, and increased minimum wages would matter. However, while multiple studies have focused on the wages of immigrants and minorities in precarious work, and others have examined turnover in certain firms or industries, relatively little work has focused on the job tenure of white servers in the restaurant industry, even though they constitute about 72% of this large and growing occupational category which is known for unusually high turnover rates. Unlike most other employees outside of restaurant work, servers rely on tips from their customers for the bulk of their earnings. However, the tipped minimum wage itself also constitutes a portion of server earnings. Since the tipped minimum wage varies across states, we can observe how differences in that law affect one key feature of their work lives—job tenure. This, in turn, can add to the evidence on what could be done to lessen the burden of precarious work for the 1 of 111 Americans employed in this occupation (United States Department of Labor 2014).

Sociologist Hollister's (2011) review of job stability literature "shows that evidence of declines in employment stability is stronger than originally portrayed and that therefore the field deserves renewed attention" (Hollister 2011: 305). Another sociologist, Vallas (2015), writes that "the patterns of job instability within the United States... remain poorly understood" (Vallas 2015: 468). Further, Vallas (2015), paraphrasing anthropologist Ho's (2009: 374) work, describes how most businesses deem "employer loyalty as a quaint, antiquated notion that has no place within the contemporary capitalist economy" (Vallas 2015: 465). Clearly, something in the tenor of American work life has changed over the past several decades when considering the low employment stability of many wage-earning workers. Although "precarious labor" has many facets, one such facet—low job tenure—is very possibly an outcome of another key facet of precarity—low wages. Dube et al. (2013), Batt, Lee, and Lakhani (2014), and Liu et al. (2016) all show that higher minimum wages—at least to an extent—reduce employee turnover and increase employee tenure. However, among these studies, only the former two cover restaurant workers, and the closest to studying tipped restaurant servers specifically is Batt, Lee, and Lakhani (2014) who split their research groups into "front of house" and "back of house" restaurant workers. My study which looks specifically at restaurant servers'—an occupational group highly prone to turnover—responses to an online survey in 2006 is thus valuable. Additional research into the distinct causes of precarious work outcomes such as low job tenure is much needed in the context of the contemporary American economy which continually values profits over people. As Vallas (2015) concludes, "Questions abound, and answers are few" (Vallas 2015: 468).

My study examines differing state tipped minimum wage policies' potential effects on white restaurant server job tenure, as restaurant servers exhibit among the highest rates of job turnover—and therefore among the lowest rates of job tenure—among various wage-earning occupations. Specifically, restaurants servers' *voluntary* turnover rate averaged at 50.3% in 2015, meaning half of restaurant servers left their jobs willingly during 2015 (Bureau of Labor Statistics 2016: 29). Low job tenure among restaurant servers is a concern for both the workers who feel the need to change jobs frequently and for restaurant owners/managers who deal with constant staff changes and costly job training. My statistical analysis of tipped minimum wages' effects on white restaurant server job tenure controls for gender, age, marital status, county unemployment levels, city population, and average percentage of tips received. By investigating the tipped minimum wages' potential effect on white server job tenure, this study shall contribute to the small but growing number of studies of precarious job tenure and its determinants.

The literature review first summarizes research about the conditions that affect both job turnover and job tenure in low wage occupations, and then describes the occupation of restaurant serving as a kind of precarious work. The study then focuses on testing how state tipped minimum wage laws affect job tenure in restaurant serving, and it concludes with implications.

Literature Review

The Restaurant Serving Occupation

In 2014, over 2 million waiters and waitresses were working in the United States, meaning that if one considers all individuals 18 and older, restaurant servers comprised roughly .9 percent of the adult (18 and older) 2014 U.S. population (United States Department of Labor 2014). This means that 1 out of every 111 individuals was working as a restaurant server in 2014 America. However, this occupation presents special circumstances. Specifically, restaurant servers—unlike fast food employees who are also a sizable group—rely on tips directly for their financial survival. As Jayaraman (2016) describes this, "[Workers'] dependency [on tips] creates an untenable economic situation:

workers' income fluctuates by year, season, week, shift, and hours. It also fluctuates with the varied whims of customers" (Jayaraman 2016: 37). The fact that servers largely do not rely on their employers but rather on customers for the bulk of their earnings leads to a unique type of financial vulnerability not seen in most wage-earning professions.

The history of the tipped wage system in American society quite clearly shows that tip-reliant occupations such as restaurant serving are structured legally to create a precarious environment for workers. Jayaraman (2016) writes, "Thus, the federal minimum wage for tipped workers has gone from $0, in the first minimum wage law passed in 1938, to $2.13, over a period of almost 80 years" (Jayaraman 2016: 35). Beginning in 1966, Congress ensured the tipped wage rose as a percentage of the standard minimum wage, peaking at 60% in 1980. But then, as Jayaraman (2016) writes: "This changed in 1996, however, when the National Restaurant Association... struck a deal with Congress, arguing that they would not oppose a very modest minimum wage increase for other workers as long [as] tipped workers' wages remain frozen forevermore, no longer increasing with the overall minimum wage" (Jayaraman 2016: 35). Servers currently earn a federal "tipped" minimum wage of $2.13, but states can set higher minimums. For instance, in Illinois, the tipped minimum wage is $4.95, and some other states have higher amounts. In 2015, 17 states still had a tipped minimum wage of $2.13.

If a waiter/waitress does not earn up to the state minimum wage—in many states this is still $7.25 per hour—the Fair Labor Standards Act (FLSA) mandates that managers give "tip credit" to the servers, meaning they must pay the difference between a server's earned tipped wage plus tips and the state minimum wage (United States

Department of Labor 2013). Still, some researcher observations indicate that waiters/waitresses are not often compensated for poor tipping, and so tips comprise the majority of server earnings (The Restaurant Opportunities Centers United 2012; Jayaraman 2013, Jayaraman 2016). One tri-city study by Bernhardt et al. (2009) of over 4000 minimum wage workers showed that 30 percent of tipped workers in the sample were not paid a base tipped wage in the first place, and on top of this, 12 percent of the interviewed tipped workers had managers who stole tips from them (Bernhardt et al. 2009: 3).

Some research has shown that correlations exist between certain specific tip-getting strategies and receiving higher tips. Researchers Michael Lynn and Michael McCall (2009), synthesizing specific tip-raising strategies identified by past researchers, show that these strategies can be generalized to an extent (Lynn and McCall 2009: 207). To do this, they use the same data I am using in my study: a 2006 online survey they distributed which received over 2000 responses from U.S. restaurant servers alone. Lynn and McCall show—through running regression analysis—that many serving strategies for increasing tips are generalizable, including telling jokes to customers, squatting next to the table, calling the customer by name, touching the customer, smiling, predicting good weather, drawing on the check, and more. Lynn and McCall (2009) conclude that "managers have an opportunity to increase their servers’ tip incomes by training them to engage in these behaviors" and that "common sense and prior research (Lynn 2002, 2003) indicate that doing so will help to reduce turnover" (Lynn and McCall 2009: 207).

However, a wide breadth of empirical research shows the arbitrary criteria of customers' tipping behaviors and the weak relationship between general quality of service provided by servers and customer tips. Social psychologist Mary B. Harris (1995) conducts interviews with over 100 servers and customers, concluding that although the quality of service a server delivers increases tips received, poor food quality and seating can drive down tips (Harris 1995: 725). Similarly, sociologist Michael Lynn (2000) conducts a meta-analysis of 7 published and 6 unpublished studies regarding over 2500 dining parties at over 20 different restaurants (Lynn 2000: 203). His findings suggest that although the quality of service provided by a waiter/waitress correlates with customer tip size, such a relationship is weak when other factors are taken into consideration. Customers were found to leave higher tips over factors outside of waiter/waitress control such as food quality (Harris 1995: 725; Lynn 2000: 203). Other factors included customers waiting a long time for a beverage (partially in a waiter's/waitress' control depending on busyness of restaurant), being seated in a bad location, (Harris 1995: 725) and customer mood (Lynn 2000: 203). Additionally, Lynn's 2005 study shows that customers strongly tend to tip less if their server is black (Lynn 2005: 87). Thus, aside from quality of service, attitude, and perhaps specific strategies that Lynn and McCall (2009) identify, a multitude of largely arbitrary factors may raise or lower a customer's tip.

Restaurant Serving as Precarious Labor

Guy Standing's (2014) many criteria of "precarious labor," provide a good framework to contextualize the lives of restaurant servers in the United States. These characteristics include low wages (possibly below legal levels), a lack of benefits, job instability, a lack of scheduling power, a lack of an occupational narrative to give to life, and occasionally working off the clock. The first characteristic, low wages, is especially an issue for restaurant servers. The United States Bureau of Labor Statistics (2011) has reported that nearly 39% of restaurant servers make at or below minimum wage, this proportion being higher than any other occupation in the United States (Bureau of Labor Statistics 2011). Additionally, full-service workers use $9.5 billion in public assistance annually (Jayaraman 2016: 37).

The second characteristic of precarious labor is instability: "Whereas the proletarian norm was habituation to stable labour, the precariat is being habituated to unstable labour" (Standing 2014: 17). Indeed, rates of layoffs for the "accommodation and food services" industry in 2015 was on the higher-end relative to all other industries: employers laid off 19.5% of workers (Bureau of Labor Statistics 2016: 31). Additionally, the accommodation and food services industry led all other industries in voluntary turnover, averaging at 50.3% of all workers quitting in 2015 (Bureau of Labor Statistics 2016: 29). Overall, the total 2015 turnover rate for those in accommodation and food services—combining layoffs, quits, and other departures such retirement, transfers, and death—was 72.1%; a very high figure when compared to the total private sector's total turnover rate of 45.9% (Bureau of Labor Statistics 2016: 27). Of course, this figure is high at least partially because a fair number of restaurant servers are teenagers who often leave a job to look for new work or to go to college. Still, it seems likely that much of the higher turnover and lower job tenure in the restaurant industry may be due to American restaurant work fulfilling many aspects of "precarity."

Adding to the precarity of restaurant work is the disappearance of benefits which the American working class once enjoyed. As Standing (2014) writes, "This is a structural change. The precariat lacks access to non-wage perks, such as paid vacations, medical leave, company pensions and so on" (2014: 18-19). The implications of this are staggering in the case of restaurant workers.

With regards to sick leave, ROC United's (2012) survey of over 4300 restaurant workers across the country states that "90 percent [of workers] lack paid sick days and 90 percent do not receive health insurance through their employers" (ROC United 2012: 3). Additionally, because approximately 26.8% of all female restaurant workers are mothers and more than 10% are single mothers, lack of health care and paid sick leave disproportionally disadvantages female servers over male servers" (ROC United 2012: 3), especially considering the cultural expectations that women "should" do the care work. Gender considerations aside, the consequences of restaurant servers needing to work—to handle the American customer's food—while sick should be both clear and troubling.

The occupation of restaurant server also strongly demonstrates another key aspect of precarity: a lack of scheduling power. As Standing (2014) writes, "The precariat cannot demarcate life into blocks of time. It is expected to be available for labour and work at all times of the day and night" (Standing 2014: 22-23). Indeed, the Restaurant Opportunities Center United (ROC United) reports that restaurant servers routinely and ubiquitously experience extremely inconsistent scheduling (ROC United 2012: 8).

Kaitlyn Matulewicz (2015) further corroborates this in her review of literature regarding restaurant servers, writing, "Inadequate employment standards laws... do not inhibit the organization of restaurant work, in such a way that workers' schedules are unpredictable and can vary from day to day. Restaurant workers go to work not always knowing how long their shifts will be or whether they will even start work at all" (Matulewicz 2015: 415). This lack of scheduling stability further weakens workers capacity to live fulfilling lives both on and off the job, especially as inconsistent hours worked means inconsistent base pay—on top of already inconsistent tips which constitute the majority of servers' earnings.

Standing (2014) also asserts that the precarious worker has a "lack of an occupational identity or narrative to give to life" (Standing 2014: 22). As servers generally lack opportunities for promotion, there is not a narrative of job "progress" they can ascribe to their work. Many servers, at least in Denstedt's (2008) study, viewed waiting tables as "dead-end" work (Denstedt 2008: 118-119). Jayaraman's (2016) research supports this: "Two-thirds of restaurant workers surveyed nationally reported never receiving a promotion to a higher-paying position, and even fewer reported ever being offered training necessary to move up the ladder to higher-level positions [ROC United 2011]" (Jayaraman 2016: 14).

Arguably, the very foundation of restaurant serving is at least temporarily accepting a role of servitude. Sociologist Paules (1991) describes this in her interview-based study of servers in a New Jersey restaurant, writing, "Virtually every rule of etiquette is violated by customers in their interaction with the waitress: the waitress can be interrupted; she can be addressed with the mouth full; she can be ignored and stared at; and she can be subjected to unrestrained anger… She is, in addition, the subject of chronic criticism" (Paules 1991: 138). In other words, without an extremely optimistic attitude, a restaurant server also experiences precarity due to a lack of larger fulfillment and meaning which most other jobs more readily offer.

One consequence—perhaps not commonly realized—is the high rate of harassment committed against female restaurant servers:

> A recent MSNBC review of Equal Employment Opportunity Commission (EEOC) data revealed that from January to November 2011, almost 37 percent of all EEOC charges by women regarding sexual harassment came from the restaurant industry, even though less than 7 percent of employed women work in the restaurant industry" (ROC United 2012: 4).

Additionally, in states where the tipped minimum wage is $2.13, female restaurant servers experience twice the rate of sexual harassment as compared to states where the tipped minimum wage and the non-tipped, standard minimum wage are the same (Jayaraman 2016: 38). Thus, these servers likely only endure sexual harassment for the sake of earning higher tips; for financial survival.

In summary, it is clear that restaurant serving constitutes a quintessential form of "precarious labor." As Densedt (2008) writes in the introduction to his mixed-methods study on Canadian restaurants: "Precarious employment refers to forms of work characterized by limited job security, few employment benefits, lack of control over the labour process and low-wages. Restaurant work demonstrates a range of precarious forms of employment" (Denstedt 2008: i).

Table 1. ROC United's 2011 Survey of Restaurant Workers Across the United States (ROC United 2011)

Percentage of workers surveyed in all eight regions who:	
Did not have health insurance provided through their employer	89.7%
Did not have paid vacation days	79.4%
Did not have paid sick days	87.7%
Worked while sick	63.7%
Suffered from overtime violations	46.3%
Of those being passed over for a promotion reported that it was based on race	28.0%
Reported having to do things under time pressure that might have harmed the health and safety of the consumer	34.6%
Reported that they or a family member had to go to the emergency room without being able to pay	22.6%

Influences on Job Turnover and Job Tenure

For the sake of this discussion, job turnover is the act of workers leaving their jobs in a given time frame. It can come in the form of managers and bosses terminating individuals' employment statuses or in the form of voluntary turnover wherein workers choose to quit. On the other hand, job tenure is the amount of time a given worker currently has at his/her job.

Judging from the table and discussion above, it is no surprise that the restaurant industry exhibits one of the highest employee turnover rates of any industry (Bureau of Labor Statistics 2016: 29). Restaurant servers encounter a constellation of troubles due to their legal-but-detrimental work circumstances. A general dearth of earnings, benefits, and customer respect likely all contribute to the documented high rate of voluntary quitting—about 50.3% annually (Bureau of Labor Statistics 2016: 29)—among those in the food and accommodation industry.

The conditions affecting job turnover and job tenure that are considered in this review include the gender and age of the employee, as well as the state unemployment rate and base tipped wages. I only examine white servers, as minorities are under-represented in my sample. Additionally, in one meta-analysis on correlates of employee turnover, researchers searched key journals in the organizational sciences for articles throughout the 1990s, and they ultimately "found no relationship between race and turnover despite widespread accounts that minority employees are more likely to quit" (Griffeth et al. 2000: 479).

With regards to gender, the same meta-analysis reveals that "the gender-turnover correlation indicates that their [women's] turnover rate is similar to that of men" (Griffeth et al. 2000: 484-485). The authors note that younger women exhibit higher rates of turnover, but that "women are more likely to remain as they age than are men. Perhaps domestic duties for women—who traditionally assume primary responsibility for household chores and child care—decrease as they age" (Griffeth et al. 2000: 484-485). Thus women—according to this meta-analysis—may turnover more often when younger, but as they age, they tend to not be statistically different from male workers in this regard.

Several other studies look at gender with regards to employee turnover. The first is Boles et al.'s study from 1995, examining ways to aid managers in the hospitality industry. The researchers distributed surveys to over 300 restaurant workers at 17 different mid-level and upscale restaurant in the Southeastern United States. Based on regression analysis, Boles et al. (1995) find that while education and work experience predict employee turnover, facets which employers often screen for such as age and gender do not significantly predict turnover (Boles et al. 1995: 19). However, a 2009 study of a nationally-representative sample of certified nursing assistants (CNAs) in nursing homes shows gender to be significant with regard to job tenure (Wiener et al. 2009: 208). Therefore, gender reveals mixed effects in relation to job turnover and job tenure.

Age is another demographic characteristic that is a bit tricky to consider in its effects on job tenure and job turnover. One would expect a strong relationship between higher age and higher job tenure. For instance, Butler et al.'s (2014) study regarding home care aides shows that older age predicts longer job tenure (Butler et al. 2014: 179). However, Boles et al. (1995) concludes that age does not significantly predict workers' turnover rates (Boles et al. 1995: 20).

Unemployment rate is a larger, structural factor which has entered much academic discourse regarding job tenure. It, too, is contested in its significance. Wiener et al. (2009), studying nurses' aides in nursing homes using 2004 data, writes that higher unemployment rates lead to longer job tenure because workers have fewer options to change employers. Specifically, they find that "a 1 percentage point increase in the unemployment rate increased tenure between 1.4 and 1.7 months for the subgroup and total sample of respondents, respectively" (Wiener et al. 2009: 200, 206). Butler et al.'s (2014) study of home care aides similarly finds that "more isolated areas have experienced particularly high levels of unemployment. In such a context, with fewer job opportunities to attract them away, it is not surprising that home care workers in rural areas would be more likely to stay in their home care jobs" (Butler et al. 2014: 180). Of course, this observation could speak to how a town being "rural" may uniquely affect job tenure outside of rural towns' generally higher unemployment rates.

Lambert et al. (2001), reviewing previous social-scientific studies of labor, critiques the idea that the unemployment rate translates into workers' perceptions of local job opportunities:

> Some studies have used local unemployment rate as a measure of alternative employment opportunities... However, this may not adequately measure an individual person's availability of alternative unemployment opportunities. A person may be unaware of the unemployment rate, or the unemployment rate may not reflect the individual's field of employment. (Lambert et al. 2001: 238)

The nursing assistants in Wiener et al.'s (2009) study have more limited job options than waiters and waitresses, so it is very possible that the unemployment rate's effect on tenure/turnover may be more readily apparent to workers in smaller job markets such as nursing assistants than to waiters and waitresses who need not travel far to find another restaurant.

Finally, higher wages have more or less consistently shown to decrease job turnover and increase employee tenure. Researcher Morris (2009), citing various economic/labor theorists, writes, "If wage levels and benefits do not sufficiently compensate for adverse working conditions such as risk of injury and job stress as well as travel and other work-related costs, workers can increase their utility by changing jobs or quitting (Campbell, 1994; Clark & Oswald, 1996; Van Ophem, 1991)" (Morris 2009: 637). According to this line of reasoning, the more stressful and precarious the job position, the greater wages need to be in order to lower worker turnover rates and therein increase worker job tenure.

Morris (2009), in her survey-based study among home care workers in Maine, finds that "wages... remain statistically significant and negatively correlated to turnover even after controlling for job, worker, and labor market factors (Morris 2009: 645). Specifically, she finds that a 20% increase in the minimum wage reduces worker turnover by 20% while ensuring workers receive full-time hours reduces turnover by 21% (Morris 2009: 645). Morris' study is one of many which show that when workers earn more, they tend to quit less. And by direct consequence, job tenure increases as well.

Various other studies also show how higher wages lower worker turnover and increase worker job tenure. Butler et al.'s (2014) longitudinal survey/interview study—beginning in 2008—on home care aides in Maine reports that "though there was not a wide range in the wages earned by study participants, higher wages did predict longer job tenure, further indicating the importance of adequate compensation" (Butler et al. 2014: 179). The previously mentioned study of home care aides by Wiener et al. (2009)—this one using a nationally-representative sample—finds that "increasing wages and benefits has a consistently positive effect on job tenure" (Wiener et al. 2009: 200).

Additionally, Harris (2010), in a study on retention of McDonald's newly-hired employees (n = 454) at 6 McDonald's restaurants in the state of Georgia, shows that wage increases at McDonald's restaurants across the nation in-part lead to increased job tenure (Harris 2010: 16). Three restaurants were in the treatment group while the other 3 restaurants were in the control group. However, the treatment group did not solely receive higher wages. They also underwent stricter screening in order for management to hire employees with attitudes and skill sets more likely to lead to longer job tenure

(Harris 2010: 71). Further, they received more thorough and involved job orientations both initially and a month into the job in order to lessen work stress resulting from a lack of knowledge (Harris 2010: 72-73). Further, it should be noted that management in the treatment group did not provide wage increases immediately, but rather after 90 days, based on employee performance levels (Harris 2010: 73). Using z-tests and comparing descriptive statistics, Harris (2010) shows that the treatment group experienced a lower turnover rate of 22.4% compared to the control group's 72.1%. This disparity meant that the treatment group's restaurant owners only paid $11,820 to replace employees while the owners of McDonald's restaurants in the control group spent $34,672 to replace employees; implementing these policies saved these fast food restaurant owners $22,852 during the experiment (Harris 2010: 123-124). As Harris (2010) writes, "Total replacement cost for the treatment group was substantially lower than the overall replacement cost of the control group. As cost was reduced, the opportunity to improve profits increased" (Harris 2010: 117). Although this study did not address tipped wages due to its context of the fast food industry, it shows that higher wages are likely at least a part of reducing employee turnover and therein increasing employee tenure.

And finally, Batt, Lee, and Lakhani (2014) examine conditions of both front-of-house and back-of-house workers in the restaurant industry, conducting a phone survey with over 1000 managers across the country. To conduct the national survey, researchers made phone calls to 1150 restaurants across the United States. Managers discussed various types of information including customers served, restaurant characteristics, and information regarding workers. The latter topic included "staffing and selection, training and development, compensation, and the organization of work" (Batt, Lee, and Lakhani 2014: 5). It should be noted that the researchers "surveyed restaurants in the 33 largest metropolitan areas of the country, where wages and the cost of living are likely to be higher than in smaller cities and towns—and where higher competition is likely to drive employers to invest more in employees in order to compete more effectively on quality and service" (Batt, Lee, and Lakhani 2014: 1). The authors thus note that the average conditions of restaurant workers found in their study are likely better than those of a nationally representative sample (Batt, Lee, and Lakhani 2014: 1). The researchers perform a multivariate regression analysis, finding that for "front of house" workers (e.g., servers, bartenders, hosts, bussers, etc.), hourly wages rank first in predicting job tenure and third in predicting job turnover (Batt, Lee, and Lakhani 2014: 19). Therefore, Batt, Lee, and Lakhani (2014) further suggest that wages impact the job tenure of front-of-house workers in the restaurant industry:

Table 2 Batt, Lee, and Lakhani's (2014) Findings of Top Predictors of Turnover and Tenure Among Front-of-House Workers (Batt, Lee, and Lakhani 2014: 19)

Rank	Turnover	Tenure
1	Job Security	Hourly Wages
2	Promotion from Within	Tips
3	Hourly Wages	Work Hours
4	Discretion	Promotion from Within
5	Benefits	Discretion

Some studies have focused on the effect of legislated minimum wage increases on job turnover. Liu et al. (2016) examine youth labor markets using U.S. county-level panel data from 2000 to 2009, finding that across all three age subgroups within the study, ranging from 14 to 24 years of age, worker turnover significantly decreases when minimum wages are higher. The researchers conclude, "Our results add to a small but growing number of studies in suggesting that the most consistent impact of the minimum wage may well be its negative influence on worker turnover rates" (Liu et al. 2016: 19).

In a similar approach, Dube et al. (2013) examine minimum wage effects on turnover among teens and restaurant workers. Using the Quarterly Workforce Indicators (QWI) dataset, they examine 1,181 cross-county pairs. They delineate 5 dependent variables: earnings, employment, accessions (hires), separations, and turnover rate. To control for spatial heterogeneity, these researchers analyze pairs of neighboring counties, where each county is on the opposite side of a state line relative to another county. "Measuring labor market outcomes from an immediately adjacent county provides a better control group, since firms and workers on either side are generally affected by the same idiosyncratic local trends and experience macroeconomic shocks at roughly the same time" (Dube et al. 2013: 9). The authors conclude:

> ...our border-discontinuity estimates find strong positive responses of earnings to a minimum wage increase. This rise in earnings is met with a change in the employment stock that is indistinguishable from zero. However, we find clear evidence that employment flows (hires and separations) fall strongly in response to the policy change. And these patterns hold whether we consider a high-impact demographic group (teens) or a high-impact industry (restaurants) (Dube et al. 2013: 20).

Their research reveals that "separations, hires, and turnover rates for teens and restaurant workers falls substantially following a minimum wage increase" (Dube et al. 2013: 2). Specifically, they find that a 10% increase in the minimum wage decreases turnover for teens and restaurant workers by 2.0% percent and 2.1% respectively.

Collectively, these studies suggest a link between higher wages, reduced turnover, and therein higher job tenure. As Dube et al. (2013) concludes, "Clearly, minimum wage policies substantially reduce turnover and increase job stability, even without affecting overall employment levels for highly affected groups, such as teens" (Dube et al. 2013: 31).

Design, Data, and Methods

Design

Since the literature on low wages suggests that higher minimum wages reduce turnover and increase job tenure in many occupations, my study asks specifically whether or not tipped minimum wages varying state to state have a relationship with job tenure. While it is apparent tips make up much of servers' earnings and thus positively influence server job tenure, it is very possible that higher tipped minimum wages also positively impact tenure. While a study such as Dube et al. (2013) finds a relationship between higher wages and longer job tenure in the restaurant industry, it looks at restaurant workers in general as opposed to just tipped restaurant servers who especially experience many forms of precarity. My data source is a very large convenience sample—which is largely representative of the broader 2006 server population—which allows the examination of nearly 1700 online survey responses from restaurant servers themselves.

Although my data lacks some variables related to job tenure which Batt et al. (2014) include (e.g., work hours and actual hourly wages as opposed to tipped minimum wages), and it does not have the sophisticated cross-county-controlling method of measurement which Dube et al. (2013) use, it features county and city-based geographical variables, and it looks at restaurant servers specifically—more so than Batt, Lee, and Lakhani (2014) with their broader designations of "front of house" and "back of house" restaurant workers. It shall thus be able to contribute to the growing number of important studies and conversations regarding wages and job tenure. Based on this and other literature mentioned previously, my study aims to compare states with higher tipped minimum wages to those with lower tipped minimum wages and observe the differential effects on job tenure—all while controlling for gender, marital status, age, county unemployment levels, city population, and average server tips. It is likely that states with a higher tipped minimum wage will exhibit higher rates of job tenure due to servers' greater financial security in those states. Additionally, geographical variables such as city population and county unemployment make my model more robust and compelling. Finally, incorporating the average percent tips variable accounts for server tips—another large part of restaurant servers' financial security. By controlling for the average tip percentages servers report receiving, my model shows the unique effect of state tipped minimum wages on server job tenure.

Data: Source and Sample Composition

A long search for a data source eventually led me to contact Dr. Michael Lynn, a professor of consumer behavior and marketing at the Cornell University School of Hotel

Administration who has published over 35 published papers regarding social-psychological factors which affects server tips in restaurants. After brief back-and-forth, Dr. Lynn generously provided me with an SPSS dataset from a large online survey he conducted in 2006,

Lynn and McCall (2009) well describe how they obtained the 2006 survey data which this study shall employ:

> Current and former restaurant servers completed an online survey about their experiences on and opinions of their job. Participants were recruited by sending invitations to students, as well as to members of commercial consumer lists (DataCorp) and panels (Zoomerang) who indicated that they were servers, and to people on Facebook.com and Myspace.com whose profiles indicated they were servers. We also asked for recruitment help from industry managers, websites that attract servers (e.g., waiterrant.net), and survey respondents. (Lynn and McCall 2009: 200)

Therefore, the cases in this data comprise a convenience sample, meaning that one cannot truly expand findings to the entire population, but he/she can still make useful inferences and observations.

It should be noted that I eliminated extreme outliers for all variables in my model. This process removed less than 50 cases in total. Additionally, I deleted cases where the server worked or was working in a restaurant where wait staff and tips were atypical (e.g., fast food chains such as McDonalds, Subway, Panera Bread, etc.). Also, I utilized listwise deletion for missing cases; SPSS deleted any cases with a missing value on any variable for the regression. Therefore, the regression ultimately included 1694 cases while several variables in the regression had 1800 or more cases.

A brief analysis of the sample in SPSS reveals that it is not representative of the larger restaurant server population from 2006 with regards to race. As both Blacks and

Hispanics are underrepresented in my sample, I determined that solely studying my overrepresented subgroups of whites would suffice for this research. Overall, given the general underrepresentation of minorities in my sample data, studying the large subpopulation of whites exclusively seems to be the best option.

Table 3 Racial Composition of Waiters/Waitresses (Bureau of Labor Statistics 2007)

My Sample from 2006:	BLS Reported Stats for 2006
Asian: 4.5%	Asian 5.3%
Black: 1.4%	Black: 7.0%
Hispanic: 2.4%	Hispanic: 14.3%
White: 91.6%	White: 71.5%

The survey data sample much more closely represented the gender composition of restaurant servers in 2006 America:

Table 4 Gender Composition of Waiters/Waitresses (Bureau of Labor Statistics 2007)

My White Sample from 2006:	BLS Reported Stats for 2006:
Males: 30.6%	Males: 28.5%
Females: 69.4%	Females: 71.5%

The median age of servers in my sample also parallels the national median age for servers in 2006. My white sample's median age, 26, is close to 26.1, the Bureau of Labor Statistics' median reported age for restaurant servers in 2011 (Bureau of Labor Statistics 2012: 6).

Finally, my sample is mostly reflective with regards to the proportion of servers by state:

Table 5. Percentages of Waiter/Waitress Population/Sample State by State (Bureau of Labor Statistics 2012)

State	Server Percentage Based on BLS 2011 Data	Server Percentage Based on My 2006 Sample	Difference Between 2006 Sample and 2011 BLS Data Percentages
Alabama (AL)	1.21	1.13	-0.08
Alaska (AK)	0.16	0.32	+0.16
Arizona (AZ)	2.14	1.85	-0.29
Arkansas (AR)	0.77	0.81	+0.04
California (CA)	10.19	7.41	-2.78
Colorado (CO)	1.93	2.26	+0.33
Connecticut (CT)	1.13	1.54	+0.41
Delaware (DE)	0.35	0.41	+0.06
Florida (FL)	7.78	5.29	-2.49
Georgia (GA)	3.04	2.17	-0.87
Hawaii (HI)	0.61	0.18	-0.43
Idaho (ID)	0.37	0.36	-0.01
Illinois (IL)	3.37	3.93	+0.56
Indiana (IN)	2.23	1.67	-0.56
Iowa (IA)	1.09	0.81	-0.28
Kansas (KS)	0.96	1.08	+0.12
Kentucky (KY)	1.26	0.90	-0.36
Louisiana (LA)	1.47	1.81	+0.34
Maine (ME)	0.49	0.41	-0.08
Maryland (MD)	1.97	2.31	+0.34
Massachusetts (MA)	2.47	3.84	+1.37
Michigan (MI)	3.15	2.80	-0.35
Minnesota (MN)	2.01	2.03	+0.02
Mississippi (MS)	0.71	0.18	-0.53
Missouri (MO)	2.19	2.40	+0.21
Montana (MT)	0.38	0.36	-0.02
Nebraska (NE)	0.70	0.45	-0.25
Nevada (NV)	1.63	0.63	-1.00
New Hampshire (NH)	0.48	0.50	+0.02
New Jersey (NJ)	2.55	2.40	-0.15
New Mexico (NM)	0.65	0.45	-0.20

New York (NY)	5.86	8.45	+2.59
North Carolina (NC)	3.13	3.03	-0.10
North Dakota (ND)	0.32	0.14	-0.18
Ohio (OH)	3.66	6.92	+3.26
Oklahoma (OK)	1.32	0.68	-0.64
Oregon (OR)	1.16	1.13	-0.03
Pennsylvania (PA)	3.84	5.47	+1.63
Rhode Island (RI)	0.38	0.41	+0.03
South Carolina (SC)	1.56	1.40	-0.16
South Dakota (SD)	0.32	0.32	0.00
Tennessee (TN)	2.01	1.99	-0.02
Texas (TX)	8.51	7.28	-1.23
Utah (UT)	0.78	0.41	-0.37
Vermont (VT)	0.20	0.27	+0.07
Virginia (VA)	2.75	3.71	+0.96
Washington (WA)	1.80	1.54	-0.26
West Virginia (WV)	0.53	0.32	-0.21
Wisconsin	1.86	2.31	+0.44
Wyoming	0.20	0.09	-0.11
Washington D.C. (DC)	0.34	1.45	+1.11

*2011 BLS data was used as a point of comparison because 2011 was the first year such "Occupation Profiles" were available: http://www.bls.gov/oes/tables.htm

Most server populations in my sample are proportionally close to those in the entire state server populations. It must be noted that because the Bureau of Labor statistics did not have "occupation profiles" before 2011, the "real" percentages my sample is being compared to are from 2011 Bureau of Labor Statistics data. Only a few states were off by several percentage points. Specifically, New York is overrepresented by 2.59% at 8.45% of the sample as compared to the real state percentage of total servers being 5.86%. This is to be expected as Dr. Lynn, the survey-maker and primary researcher for the studies deriving from this sample, works at Cornell University in New York. Additionally, Ohio is overrepresented by 3.26% at 6.92% as compared to the real percentage of 3.66%. Florida is underrepresented by 2.49% at 5.29% as compared to the total real percentage of 7.78%. Similarly, California is underrepresented by 2.78% at 7.41% as compared to its real percentage of 10.19%. As all the aforementioned states have very large populations, all their state server populations, even if underrepresented, are still quite large and thus are still mostly reflective of reality.

Further, it should be noted that my 2006 sample's median months on the job was 14 months, or about 1.2 years. This is rather similar to the national median server job tenure in 2006 which was 1.4 years (United States Bureau of Labor Statistics 2016: 10).

Data: Transforming the Dependent Variable of Months on the Job

For my dependent variable, I used a variable which represented a server's months on the job. In some cases, servers who took Dr. Lynn's survey had only been servers in the past, so those servers answered their total number of months on the job at their last restaurant. Due to a violation of homoscedasticity (constant variance) with my original model, I performed a log transform on my dependent variable of servers' months on the job. The non-logged model's scatterplots revealed this violation of homoscedasticity, as there was a funnel, meaning that variance increased with higher values in the regression. However, I remedied this through the natural log transformation of my dependent variable.

Further, the log transformation of the dependent variable served to normalize and pull in outliers in the distribution:

Chart 1. Histogram of Months on the Job (Non-Logged)

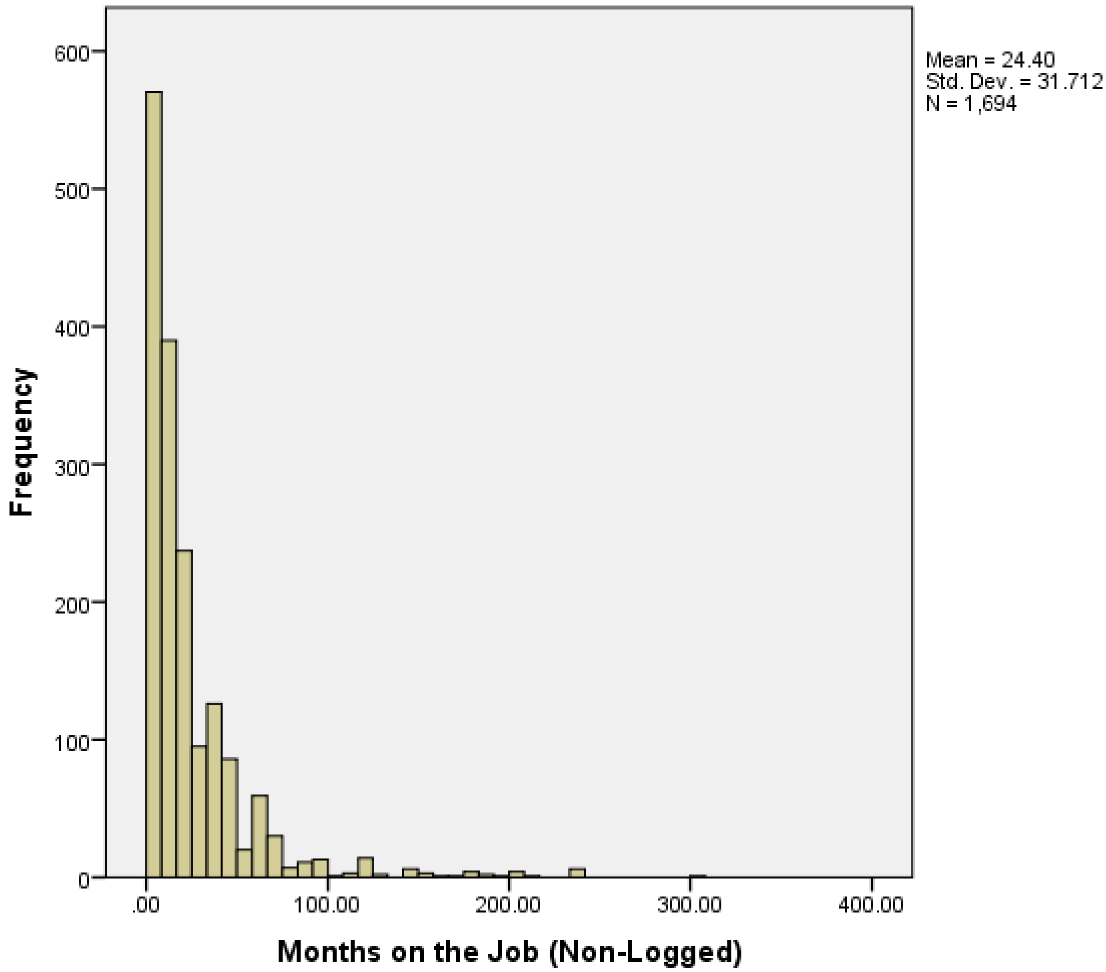
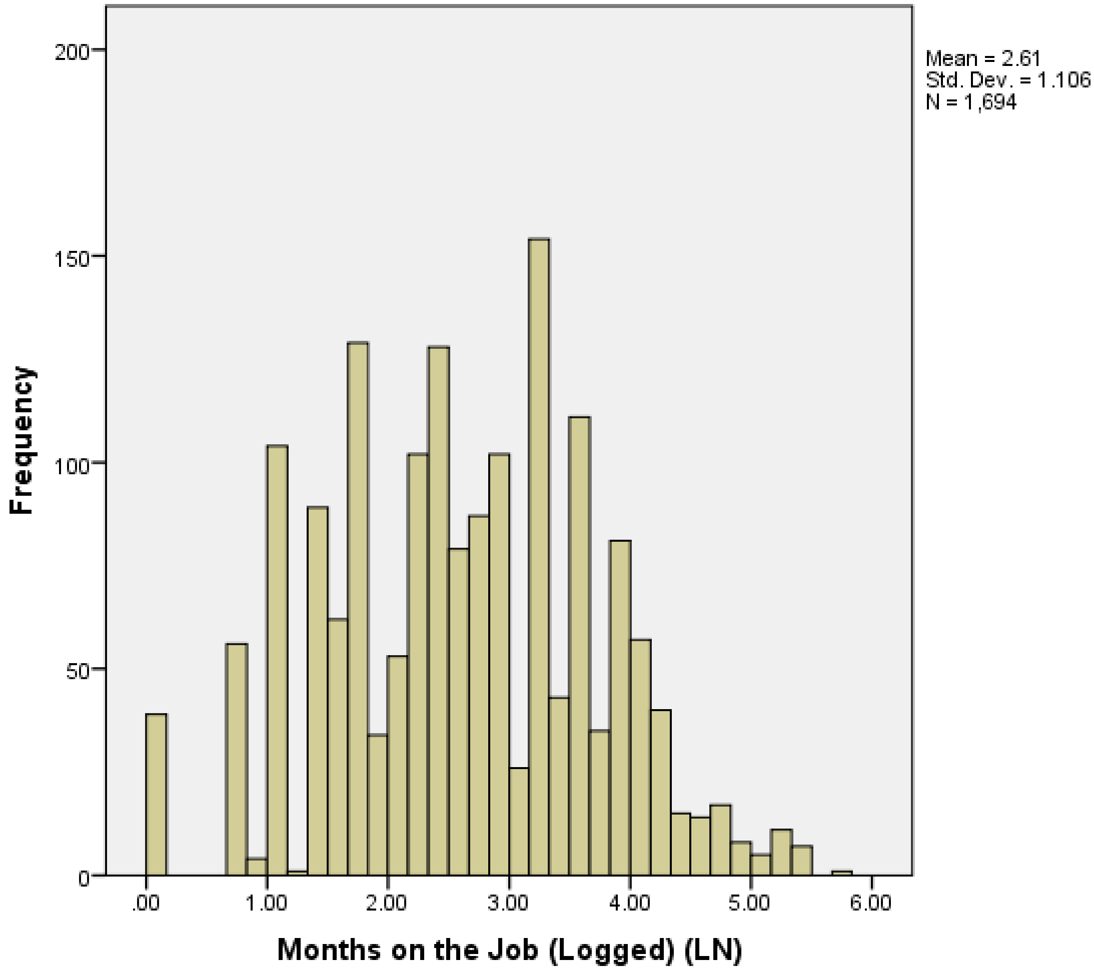


Chart 2. Histogram of Months on the Job (Logged) (LN)



Comparing the two preceding histograms, it is clear that the more normal distribution belongs to the logged version of the months on the job variable. Additionally, the logged version pulls in outliers and thus allows the regression line to better fit the data. This allows statistical inferences deriving from the regression to be more accurate. And finally, the logged dependent variable allows for a simplistic calculation of the percent changes in the dependent variable for every unit change in the independent variables.

Data: Creating City Population and County Unemployment Variables

When making the "city" variable which laid the foundation for the geographical variables in the model (i.e., city population dummy variables and county unemployment), I made some methodological decisions worth noting. First, I did not include unincorporated communities as cities on their own unless they were "Census Designated Places." This is primarily because such small communities did not have census population data listed. For this reason, I listed the nearest village, town, or city which looked similar instead of the unincorporated community. For the overwhelming majority of cases that initially were in an unincorporated community, I chose the nearest location which had population data. However, there were a handful of cases where the nearest village, town , or city seemed extremely different in some way from the unincorporated area (e.g., if it was much more affluent). In these cases, I chose the closest location—and it was always very close—which was similar in general appearance and class level. Overall, cases initially listed in "unincorporated communities" were rare. This same scheme applied for neighborhoods within cities (e.g., "Hyde Park" in Chicago was changed to just "Chicago").

Additionally, "Census Designated Places" (CDP) were kept as is unless located in a borough, village, town, or city. For example, the CDP Terramuggus—albeit not actually a case in my data—can provide an example of this coding choice. Terramuggus is a CDP within Marlborough, Connecticut, a town of 6000 people. I would not list the Terramuggus case as "Terramuggus," but rather, since it is a CDP, I would list it as "Marlborough." Although Terramuggus has a population of only around 1000 compared to Marlborough's 6000, Terramuggus is only reflective of a portion of Marlborough and perhaps some area not within the city of Marlborough. Therefore, labeling the case and population data as being and deriving from "Marlborough" is most reflective of my ultimate goal of making a city variable in order to make a city size variable. This logic always applied to CDP's except in the case of townships. If a CDP was in a township, it would remain a CDP, as townships are often completely arbitrary geographical areas which incorporate many villages and towns.

To make the city population variable, I took the city variable with the criteria described above, looked at each city/town/borough/etc. on Wikipedia, and marked down the 2010 census data listed there. I used the 2010 census data because my 2006 data is closer to 2010 than 2000, the other closest year when the U.S. government conducted the census. I then made dummy variables in multiple logical population breakpoints, including cities with less than 25,000 people, those with 25,000 to 100,000 people, those with 100,000 to 500,000 people, those with 500,000 to 1,000,000 people, those with 1,000,000 to 2,500,000 people, and finally, those cities with 2,500,000 to 9,000,000 people. Since these were dummy variables, I excluded the less than 25,000 category from my regression, meaning that the regression coefficients of the other city dummy variables are changes in months on the job—my dependent variable—relative to cities with populations under 25,000.

For my unemployment variable, I marked down county-level unemployment, as the U.S. government only records city-level unemployment for larger cities, and my sample has many cities and towns, big and small. I used United States Bureau of Labor

Statistics data from 2006. As a portion of cities in my sample existed in multiple counties, I used the 2006 unemployment rate of the first county listed in the city's Wikipedia entry. Through my observations, I determined that Wikipedia's first county listed seems to be the one where the city predominantly resides in. Even though I only recorded the first county's unemployment rate for my variable, I checked every county's listed unemployment rate to observe disparities between them. In most cases, these disparities were around 0.5%. For instance, the city of St. Charles, Minnesota is in 3 counties: Stearns, Benton, and Shelburne. Following the first-county rule I outlined above, I listed Stearns' 2006 unemployment rate of 4.0% for this case. The other unemployment rates were 4.4% and 4.3% respectively for Benton county and Shelburne county. Most cases exhibited these small disparities. Still, the disparity in cases such as this is still concerning, as the model intends to accurately reflect local conditions, and if a worker who listed a city in multiple counties lived more in a different county than the dominant one listed for a city on Wikipedia, then it could be argued that the county unemployment percentage listed is somewhat inaccurate.

Additionally, there are some cities within the sample in multiple counties where the disparities between the county unemployment rates were more concerning. One example of this is Warner Robbins, Georgia, which is in both Houston and Peach counties. While Houston County had a 2006 unemployment rate of 4.2%, Peach County's respective rate is 5.8%. Considering that the unemployment percentages in my sample range from 3.7% at the 25th percentile and 5.0% at the 75th percentile, this disparity of 1.6% between the aforementioned counties is concerning, considering my method of listing the dominant county which a city presides in. Therefore, future studies ought to, if possible, ask survey takers directly which county they live in, in addition to which city. Asking respondents for their county would mitigate any inaccuracies caused by only listing the dominant county's unemployment rate. Still, for in this study, most cities' dominant county's 2006 unemployment rates did not differ much from other counties which the city was in. As already mentioned, it seemed this percentage difference was usually around 0.5%.

A couple other technicalities of the coding process exist. Some cities, mainly in Virginia, are independent cities with no county listed. Fortunately, the United States Bureau of Labor Statistics lists independent cities' unemployment rates just as it does for counties. However, for Washington D.C., I needed to look at D.C.'s 2006 unemployment rate on a separate United States Bureau of Labor Statistics page on their website. Additionally, quite a few parishes—county equivalents—in Louisiana did not have unemployment rates listed. Even larger ones such as Orleans Parish lacked this information. As such, they were marked as "missing" in my data. Finally, during the coding process, I re-labeled the survey takers' listings of New York City boroughs as "New York City" itself for the sake of recording accurate city population data. This followed my standard coding logic of relabeling a part of a town listed by a survey respondent as the town itself. However, when it came time to record county unemployment rates, I noticed that the boroughs of New York City were county-equivalents, each with their own unemployment rates. As I had already combined the New York City borough cases into "New York City," I averaged the borough unemployment rates together, listing this average of 5.0% for any respondents who listed "New York City" as their city.

Data: Including the "Average Tip Percent" Variable

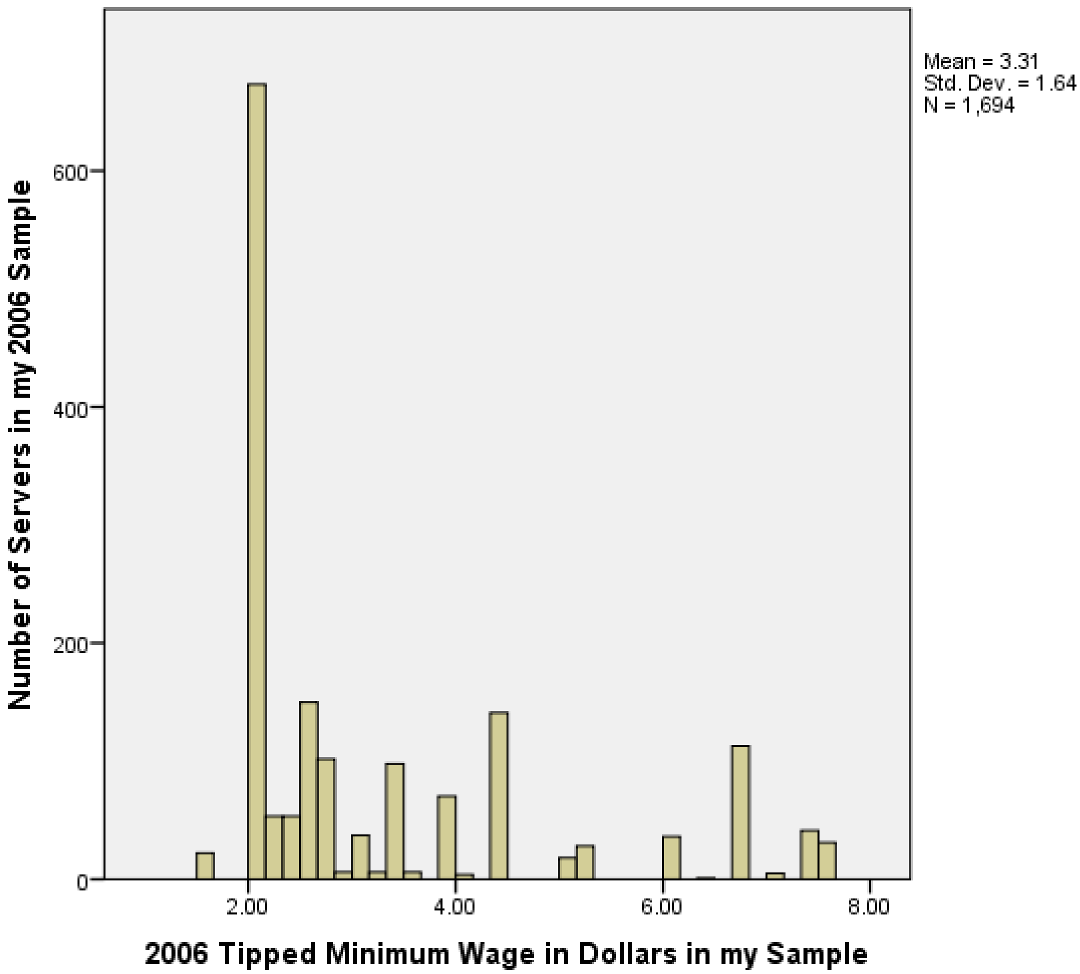
The data set included a variable which reflected the average tip percent a server received while working at his/her current restaurant. The question in Dr. Lynn's survey regarding this was: "Approximately what is the average tip percentage you receive(d) from your customers at this restaurant?" Although percentages of tips equate to different amounts of money depending on restaurant prices and customer bills, they still provide a decent indication of how much servers are earning in tips. Therefore, I incorporated this variable into my model, especially because higher tips have been shown to correspond positively with server job tenure (Batt, Lee, and Lakhani 2014: 19).

Data: Creating Tipped Minimum Wage Variable

I constructed the tipped minimum wage variable in my data by recoding each respondent's state into the tipped minimum wage value for that state in 2006. Although this method underestimates some of the tipped wages for servers who have actually received promotions and thus earn higher than the base tipped wage, it will not affect the data much, as it is well-established that restaurant servers rarely receive promotions. Jayaraman's (2016) research grounds this claim well: "Two-thirds of restaurant workers surveyed nationally reported never receiving a promotion to a higher-paying position, and even fewer reported ever being offered training necessary to move up the ladder to higher-level positions [ROC United 2011]" (Jayaraman 2016: 14). Additionally, servers who are promoted may not necessarily remain servers. As the above quote suggests, some promoted servers may move up to a managerial position.

After recoding the state responses to tipped minimum wages for 2006, the distribution of wages in the sample was as follows:

Chart 3. Distribution of State Tipped Minimum Wages Among Servers in my Sample



The minimum state tipped minimum wage was $1.59 (Kansas had below the federal tipped minimum wage in 2006) while the maximum was $7.63. The mean was $3.31 and the median was $2.63. Thus, many cases were $3 and below.

I then categorized the tipped minimum wage variable into low and high categories. This division is reflected below:

Table 6. Tipped Wage Categorized Variable Frequency

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	$1.59 to $3.00	1059	62.5	62.5	62.5
	$3.01 to $7.63	635	37.5	37.5	100.0
	Total	1694	100.0	100.0	

This division seemed ideal as there were several states with below a $3 tipped minimum wage in 2006, these wages below $3 not being so different from the federal tipped minimum wage of $2.13. Anything above $3 seemed like a good breakpoint, as an additional 2006 dollar is likely a meaningful difference to a worker who works many hours a day.

Further, this below/above $3.00 coding decision benefits my analysis in two other ways. If the categories were $2.13 versus anything higher, then those states where the 2006 tipped minimum wage was barely above $2.13 would be in my "high" wage category. These states—ones where the 2006 tipped wage was above $2.13 but below $3.00— include Arkansas ($2.58), Delaware ($2.23), Maryland ($2.38), Massachusetts ($2.63), Michigan ($2.65), New Hampshire ($2.38), Pennsylvania ($2.83), Rhode Island ($2.89), Oklahoma ($2.58), and Wisconsin ($2.33) (United States Department of Labor 2005). Therefore, not only does this $3.00 dividing line serve to capture states where the 2006 tipped minimum wage was still very low and close to the federal tipped minimum wage of $2.13, but it also allows for much more geographic diversity in the low tipped wage category. The upcoming table shows in full the states' 2006 tipped minimum wages and whether they fall below the $3.00 mark or land somewhere above it. Please note that the 2006 state tipped minimum wages below pertain to restaurant servers, as some states had/have differing tipped wages for different types of tipped workers (e.g., hotel service workers, restaurant servers, etc.):

Table 7. States in 2006 Split by Low and Higher Tipped Minimum Wages

2006 Tipped Minimum Wage Below $3.00	2006 Tipped Minimum Wage Above $3.00
Alabama ($2.13)	Alaska ($7.15)
Arizona ($2.13)	California ($6.75)
Arkansas ($2.58)	Connecticut ($5.23)
Colorado ($2.13)	Florida ($3.38)
Delaware ($2.23)	Hawaii ($6.50)
Georgia ($2.13)	Idaho ($3.35)
Indiana ($2.13)	Illinois ($3.90)
Kansas ($1.59)	Iowa ($3.09)
Kentucky ($2.13)	Maine ($3.09)
Louisiana ($2.13)	Minnesota ($5.25)
Maryland ($2.38)	Montana ($4.00)
Mississippi ($2.13)	Nevada ($5.15)
Missouri ($2.13)	New Jersey ($3.09)
Massachusetts ($2.63)	New York ($4.35)
Michigan ($2.65)	North Dakota ($3.45)
Nebraska ($2.13)	Oregon ($7.50)
New Mexico ($2.13)	Vermont ($3.65)
New Hampshire ($2.38)	Washington ($7.63)
North Carolina ($2.13)	West Virginia ($4.12)
Ohio ($2.13)	
Pennsylvania ($2.83)	
Rhode Island ($2.89)	
South Carolina ($2.13)	
South Dakota ($2.13)	
Tennessee ($2.13)	
Texas ($2.13)	
Utah ($2.13)	
Oklahoma ($2.58)	
Virginia ($2.13)	
Wisconsin ($2.33)	
Wyoming ($2.13)	

With regards to geography, one can see that by dividing the 2006 tipped minimum wage this way, it is not merely southern states (which largely had a tipped minimum wage of $2.13) in the "low" tipped wage category. Within this "low" category, there are states in the northeast such as Delaware, Massachusetts, New Hampshire, Pennsylvania, and Rhode Island. There are also Midwestern states included such as Indiana, Michigan, Ohio, and Wisconsin. Additionally, some Western states—such as Colorado, New Mexico, and Utah—fall into this category. Therefore, when my tipped wage dual-category variable shows significance and has a sizable coefficient with regards to its impact on job tenure, I can express with more certainty that this effect interpretation is not likely conflated with the potential effect which being in a Southern state may have on job tenure.

Descriptive Statistics

Table 8. Descriptive Statistics

	Minimum	Maximum	Mean	Std. Deviation
Age	16	66	28.7	8.7
Sex	.00	1	.70	.46
Married	.00	1	.26	.43
County Unemployment	1.7	9.9	4.4	1.03
City Population	75	8,175,133	478,818	1,314,150
Average % Tip	1	35	16.7	3.9
Tipped Minimum Wage (Interval)	1.59	7.63	3.31	1.64
Months Current (Non-Logged)	1	300	24.4	31.7
Valid N (listwise)	1694			

Rounded descriptive statistics for my variables are pictured above. The mean age in my sample is 28.7, with the youngest server being 16 and the oldest being 66. For sex, the mean was .7, indicating that roughly 70% of my sample is women. Only 26% of my sample is married. County unemployment's mean is 4.4%, with 1.7% being the minimum and 9.9% being the maximum. Although this range of county unemployment is large, the standard deviation is only 1.03, so the distribution is fairly centered around the mean. City population has a range from 75 people to 8,175,133 people. While the mean of all city populations of servers is 478,818, the high standard deviation of 1,314,150 shows that the population distribution is spread out. The "Average % Tips" variable has a minimum of 1 and a maximum of 35. The mean tip percentage was 16.8, and the somewhat small standard deviation of 3.9 shows that the distribution is rather centralized around the mean. The state tipped minimum wage variable has a minimum of $1.59 and a maximum of $7.63, and it has a mean of $3.31. The standard deviation of $1.64 indicates that the distribution of state tipped minimum wages in my sample has many values close to $3.32. Finally, the months current variable, which shows my sample's servers' months on the job has a mean of 24.5 months. The minimum is 1 month and the maximum is 300 months. This immense range is reflected in the high standard deviation of 32.1 months.

Correlations

The correlations between my variables are as follows. Please note that "Sex" is coded "Female" = 1, "Married" is coded "Married" = 1, and the tipped wage variable is coded as a greater than $3 wage = 1. Additionally I use the logged version of my dependent variable, the non-dummy version of my city population variables, and the tipped wage categorized variable. I have marked in bold significant correlations between the independent variables and the dependent variable specifically.

Table 9. Correlations Between Variables in Model

		Months Current LN (DV)	Age	City Pop.	County Unemployment	Married	Sex	Average Percent Tip	Tipped Min. Wage < $3 vs. > $3
Months Current LN (DV)	Pearson Corr.	1	.358**	-.051*	-.012	.178**	-.050*	.109**	.083**
	Sig. 2-tailed		.000	.038	.619	.000	.040	.000	.001
Age	Pearson Corr.	.358**	1	.021	.066**	.399**	-.090**	.043	.120**
	Sig. 2-tailed	.000		.399	.007	.000	.000	.078	.000
City Pop.	Pearson Corr.	-.051*	.021	1	.130**	-.048*	-.017	.059*	.195**
	Sig. 2-tailed	.038	.399		.000	.049	.489	.016	.000
County Unemployment	Pearson Corr.	-.012	.066**	.130**	1	.033	.030	-.041	-.157**
	Sig. 2-tailed	.619	.007	.000		.168	.222	.088	.000
Married	Pearson Corr.	.178**	.399**	-.048*	.033	1	.018	-.043	.018
	Sig. 2-tailed	.000	.000	.049	.168		.458	.074	.449
Sex	Pearson Corr.	-.050*	-.090**	-.017	.030	.018	1	-.054*	-.006
	Sig. 2-tailed	.040	.000	.489	.222	.458		.027	.790
Average Percent Tip	Pearson Corr.	.109**	.043	.059*	-.041	-.043	-.054*	1	.088**
	Sig. 2-tailed	.000	.078	.016	.088	.074	.027		.000
Tipped Min. Wage < $3 vs. > $3	Pearson Corr.	.083**	.120**	.195**	-.157**	.018	-.006	.088**	1
	Sig. 2-tailed	.001	.000	.000	.000	.449	.790	.000	
	Total N	1694							

**. Correlation is significant at the 0.01 level (2-tailed)
*. Correlation is significant at the 0.05 level (2-tailed).

These correlations are, for the most part, as expected. Of concern here are the correlations between the independent variables and the logged dependent variable. First, age correlates significantly, strongly, and positively with servers' months on the job ($r = .358$, $n = 1694$, $p = < .001$). This is possibly because older servers are less likely to be upwardly mobile than younger ones who may be earning degrees alongside restaurant work, and, as such, older servers are more likely to choose to remain in such a job, therein raising their months on the job. Secondly, city population shows a significant negative correlation with servers' months on the job ($r = -.051$, $n = 1694$, $p = .038$). This is likely because in bigger towns and cities, greater opportunities to move between places of employment exist, and therefore server months on the job would tend to be lower. Third, county unemployment levels did not have any significant correlation with servers' months on the job ($r = -.012$, $n = 1694$, $p = .619$). Fourth, being married has a significant positive correlation with servers' months on the job ($r = .178$, $n = 1694$, $p < .001$). This is somewhat surprising, as Theodossiou (2002)—as mentioned earlier—shows that married women in particular have three times greater risk of terminating their job for family reasons as compared to married men (Theodossiou 2002: 739). As such, one would expect marriage to lessen servers' months on the job overall, especially in this sample where over 70% of the servers are female. Perhaps the positive correlation can be explained by the fact that married individuals tend to be older than non-married, and this is true within this sample. Because older servers tend to have more months on the job, it follows that married servers—who are frequently older—also tend to have more job tenure.

Fifth, being female (sex) is significantly negatively correlated with servers' months on the job ($r = -.05$, $n = 1694$, $p = .04$). Therefore female restaurant servers tend to have less months on the job than male restaurant servers. Although several factors may influence this, it is possible that the high rates of sexual harassment of female restaurant servers lead some female servers to change jobs more frequently than male servers, therein lessening females' aggregate tenure levels.

Sixth, average percentage of tips received has a significant positive correlation with servers' months on the job ($r = .109$, $n = 1694$, $p < .001$). This supports the idea which drives this study: that greater earnings coincide with longer job tenure. As tips are a big part of server earnings (in conjunction with tipped hourly wages), this correlation supports this hypothesis. Finally, a significant positive correlation existed between my categorical tipped wage variable and servers' months on the job ($r = .083$, $n = 1694$, $p = .001$). That is, restaurant servers in states where the tipped minimum wage exceeded $3 in 2006 were more likely to have more months on the job than restaurant servers in states where the tipped minimum wage was below $3. As discussed earlier, because of the geographical diversity which the $3 divide for this variable entails (as opposed to the $2.13 divide), it is not likely that another force is driving this correlation between higher tipped minimum wages and servers having more months on the job. For example, since not all the states in the below $3 category are in the South, it is not likely that some common Southern phenomenon where servers may stay for shorter times on the job (merely a hypothetical) is driving this correlation. Since a wide variety of states exist in both the below $3 and above $3 categories, geographically-grounded cultural differences hypothetically affecting job tenure do not likely impact this significant correlation—nor may they even exist in the first place. Therefore, this correlation suggests that higher tipped minimum wages indeed have a positive effect on servers' months on the job.

Method

For the actual method, I run an OLS regression in SPSS where the 2006 state tipped minimum wage for each state is an independent variable and logged months on the job (job tenure) is the dependent variable. As per the literature, I control for age, gender, and marital status. Further, I include a county unemployment variable, city population dummy variables, and an average percent tip variable, all of which were described above. I also conducted extensive model building with both the un-logged months on the job variable as well as the logged months on the job variable in order to determine the best model. Additionally, I examined residuals in order to assess my data's meeting and/or violation of key statistical assumptions.

Results

The OLS regression of my 2006 sample of white servers reveals the following results:

Table 10. Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.381	.145	.140	1.02547

Table 11. ANOVA

Model		Sum of Squares	df	Mean Square
1	Regression	301.107	11	27.373
	Residual	1768.764	1682	1.052
	Total	2069.872	1693	

Table 12. OLS Regression

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	1.050	.188		5.576	.000
	Age	.042	.003	.329	13.085	**.000**
	Sex	-.040	.055	-.017	-.735	.462
	Married	.122	.063	.048	1.946	.052
	County Unemp-loyment	-.017	.025	-.016	-.688	.492
	City Population 25k to 100k	-.059	.068	-.024	-.869	.385
	City Population 100k to 500k	-.025	.071	-.010	-.348	.728
	City Population 500k to 1m	-.060	.084	-.019	-.721	.471
	City Population 1m to 2.5m	-.097	.132	-.018	-.734	.463
	City Population 2.5m to 9m	-.382	.138	-.069	-2.775	**.006**
	Average Percent Tip	.027	.006	.094	4.143	**.000**
	Tipped Min. Wage < $3 vs. > $3	.107	.056	.047	1.918	**.050**

First off, it should be noted that discussion of significance levels in this regression is more to get a better feel for the prevailing variables in the model, as my sample is a convenience sample. Still, the p-values do have some pertinence, as the convenience sample is still sizable after listwise deletion ($n = 1694$), and it well reflects gender, age, and state composition of restaurant servers, as mentioned previously. The adjusted R2 for this model is approximately .14, indicating that it explains a fair amount of variance with regards to server job tenure. The regression's F-value is approximately 27.4 and its significance value is < .001.

Among the demographic control variables—sex, marital status, and age—only age is significant ($p < .001$). This is expected, as the older a server becomes, the more months on the job the server will have. Sex ($p = .462$) is insignificant in relation to servers' months on the job, controlling for other variables. Despite female servers' higher reported rates of sexual harassment, it would seem that they stay on the job for similar lengths of time as men do. And although marital status was significant in the correlation outlined above—likely due to its significant correlation with age—the above regression reveals it to be insignificant once controlling for other variables ($p = .052$).

County unemployment was also insignificant ($p = .492$). At least in this model, local unemployment levels do not inform servers' decisions to stay at their job. Much more meaningful are factors such as city size and the level of the tipped minimum wage. With regards to the city dummy variables, only one—a city of a population between 2.5 million and 9 million—is significant ($p = .006$). Controlling for other variables, servers living in a very large city with a population of 2.5 million to 9 million will have fewer months on the job than their lower-population counterparts, especially those servers in small towns of less than 25,000 people.

Additionally, the average percent tip variable was significant ($p < .001$). Therefore, controlling for other variables, higher average tip percentages increase servers' months on the job. And finally, my tipped wage categorized variable (< \$3 vs. > \$3) was significant ($p = .05$). In other words, a tipped minimum wage of greater than \$3 (in 2006) increases server's months on the job, controlling for other variables.

One accurate way of discussing regression coefficients relative to a logged dependent variable is through reporting percentage changes in the dependent variable with regards to one-unit changes in the independent variables. As only the dependent variable was transformed using a natural log (ln) transformation, I utilized the appropriate percent-change formula of [(e^$^{\text{Coefficient}}$ - 1) * 100] (Yang 2012: 2). The table below shows the percent change in logged months on the job for each unit increase of each independent variable. In the column to the right of each variable, I list the unit corresponding with the variable. In the case of an interval variable such as "Age," each unit is one year. But for a categorical variable such as "Sex," the percent change refers to if a server is female rather than male. The table is as follows:

Table 13. Percentage Change in Servers' Logged Months on Job Per One-Unit Increase in Independent Variables

Variable	"Unit"	% Change in DV	Significance Value
Age	1 year increase in server's age	4.29%	**< .001**
Sex	If server is female	-3.92%	.462
Married	If server is married	12.98%	.052
County Unemployment	1% increase in unemployment in server's county	-1.69%	.492
City Population 25k to 100k	If server's city population is 25k to 100k	-5.73%	.385
City Population 100k to 500k	If server's city population is 100k to 500k	-2.47%	.728
City Population 500k to 1m	If server's city population is 500k to 1m	-5.82%	.471
City Population 1m to 2.5m	If server's city population is 1m to 2.5m	-9.24%	.463
City Population 2.5m to 9m	If server's city population is 2.5m to 9m	-31.75%	**.006**
Average Percent Tip	1% average increase in server's tip	2.74%	**< .001**
Tipped Minimum Wage < $3 vs. > $3	If tipped minimum wage is > $3	11.29%	**.050**

Among the few significant percent changes are the variables of "Age," "City Population 2.5m to 9m," "Average Percent Tip," and "Tipped Minimum Wage < $3 vs. > $3. Starting with age, for each one-year increase in a server's age, his/her logged months on the job increase by 4.29%. Secondly, if a server lives in a city with a population of 2.5 million to 9 million, his/her logged months on the job decrease by -

31.75% as compared to a server who lives in a town of 25,000 people or less. Third, if a server receives a 1% increase to his/her average tip, his/her logged months on the job increase by 2.74%. Finally, if a server lives in a state where the tipped minimum wage is greater than $3, his/her logged months on the job increase by 11.29%. Therefore, the correlations, regression, and percent change estimations based on my 2006 data all reinforce that white servers living in states where the tipped minimum wage exceeds $3 (in 2006 U.S. dollars) stay longer at their serving jobs than servers in states with a tipped minimum wage less than $3.

To more intuitively understand results from this model, it is helpful to calculate predicted months of tenure, rather than predicted logged months of tenure. As Duan (1983) explains it, "...certain procedures, such as prediction and forecasting, on the untransformed scale... [will introduce] the problem of retransformation bias; namely, unbiased and consistent quantities on the transformed scale usually do not retransform into unbiased or consistent quantities on the untransformed scale" (Duan 1983: 605). Duan proposes a correction to the predicted values in this case, called a "smearing estimate." Citing Duan (1983), Pasta and Cisternas (2003) explain:

> The smearing estimate is based on the following idea. Although the retransformed data, exp(predicted), is a reasonable estimate of the median of the original distribution, it is not a very good estimate of the mean of the original distribution which, because of the long tail of the distribution, could be substantially larger. There are ways to account for this under the assumption that the original data are lognormally distributed, but the smearing estimate works well without assuming a specific distribution. (Pasta and Cisternas 2003: 4).

Duan's smearing factor is the accepted way to most accurately correct the bias which finding predicted values for a regression with a logged dependent variable introduces. Duan (1983) writes that "the smearing estimate can outperform parametric estimates even when the parametric assumption is nearly satisfied" (Duan 1983: 605). Duan's smearing estimate is calculated through taking the mean of the regression's exponentiated residuals and then multiplying predicted value sums by this number (Pasta and Cisternas 2004: 4-5).

In the case of my model, the mean of my exponentiated residuals was 1.5967. And so, after exponentiating my sums which corresponded with different values of my independent variables in relation to my logged dependent variable, I multiplied each by 1.5967. I kept sex constant as female, not married constant (thus no coefficient in the model since married = 1 in the coding), unemployment at 4%, and average tip at 18%. These constants reflect the median for each variable. Below are a couple examples of this calculation:

The first example is a server in my sample who is a 20 years old, living in a city of less than 25,000 people, and earning a tipped minimum wage of less than $3. The following two examples have no coefficient for city size because they are in the omitted city size dummy category of less than 25,000 population. If I were to show the math for one of the city dummy categories, I would add/subtract the corresponding regression coefficient before exponentiating and multiplying. The aforementioned server's job tenure (months on the job) is as follows:

Predicted Logged Months = 1.05 + .042*Age - .04*Female + .122*Married - .017*CountyUnemployment + 0*CitySize + .027*AveragePercentTip + .107*TippedWageLessThan$3

Predicted Logged Months = 1.05 + .042(20) - .04(1) + .122(0) - .017(4) + 0(20000) + .027(18) + .107(0)

Predicted Logged Months = 2.268

Predicted Months = e^2.268 ≈ 9.7 months

Predicted Months with Duan's Correction = (e^2.268) * 1.5967 ≈ 15.4 months

To show this same server but in a state where the tipped minimum wage is > $3, I add the regression coefficient of .107 to the sum before exponentiating and then multiplying by 1.5967:

Predicted Logged Months = 1.05 + .042*Age - .04*Female + .122*Married - .017*CountyUnemployment + 0*CitySize + .027*AveragePercentTip + .107*TippedWageGreaterThan$3

Predicted Logged Months = 1.05 + .042(20) - .04(1) + .122(0) - .017(4) + 0(20000) + .027(18) + .107(1)

Predicted Logged Months = 2.375

Predicted Months = e^2.375 ≈ 10.8 months

Predicted Months with Duan's Correction = (e^2.375) * 1.5967 ≈ 17.2 months

These two examples match the first and second rows of the table below.

Below is the table of predicted values—both using the smearing estimate and not—which correspond with my final model. The final column shows the difference in server months on the job between a state where the tipped minimum wage is greater than $3 (in 2006) versus one where said wage is less than $3. Once again, the variables held constant for the table below include sex (female), marital status (not married), county unemployment (4%), and average tip at 18%. Additionally, I excluded servers 40 years of age and older in this table, as they only account for roughly 11% of my sample. Here is the table:

Table 14. Predicted Months on the Job Focusing on Tipped Minimum Wage and Using Duan's Smearing Factor

Age	City Size	Tipped Minimum Wage	Unadjusted Months on Job	Adjusted Months on Job (Duan's)	# Months > $3 Tipped Min. Wage Adds (Duan's)
20	< 25k	< $3	9.7	15.4	
20	< 25k	> $3	10.8	17.2	**1.8**
20	25k to 100k	< $3	9.1	14.5	
20	25k to 100k	> $3	10.1	16.2	**1.7**
20	2.5m to 9m	< $3	6.6	10.5	
20	2.5m to 9m	> $3	7.3	11.7	**1.2**
25	< 25k	< $3	11.9	19	
25	< 25k	> $3	13.3	21.2	**2.2**
25	25k to 100k	< $3	11.2	17.9	
25	25k to 100k	> $3	12.5	20	**2.1**
25	2.5m to 9m	< $3	8.1	13	
25	2.5m to 9m	> $3	9.1	14.5	**1.5**
30	< 25k	< $3	14.7	23.5	
30	< 25k	> $3	16.4	26.1	**2.6**
30	25k to 100k	< $3	13.9	22.1	
30	25k to 100k	> $3	15.4	24.6	**2.5**
30	2.5m to 9m	< $3	10	16	
30	2.5m to 9m	> $3	11.2	17.8	**1.8**
35	< 25k	< $3	18.1	29	

35	< 25k	> $3	20.2	32.3	**3.3**
35	25k to 100k	< $3	17.1	27.3	
35	25k to 100k	> $3	19	30.4	**3.1**
35	2.5m to 9m	< $3	12.4	19.8	
35	2.5m to 9m	> $3	13.8	22	**2.2**

Above, one can see a wide range of predicted values, but it is clear that a higher tipped minimum wage meaningfully and positively impacts a servers' number of months on the job. Overall, servers living in a state where the 2006 tipped minimum wage was greater than $3 had an additional 1.2 to 3.3 months on the job compared to servers living in a state where the tipped minimum wage was less than $3. Although the additional months have a wide range, in most cases, the higher tipped minimum wage caused an increase of servers' months on the job of around 2 months. This 2 months estimation comes from two things. First is the fact that the majority of servers in this data are under 30 years of age; 50% of servers in this data are at or under 27 years old while 75% are under 35 years old. Therefore, one can obtain a good overall picture of months added by a higher tipped minimum wage by observing the rows corresponding with those 30 and under, as this is where the majority of cases in the data exist on the age spectrum. And among those servers 30 years old and younger, months on the job added by a higher tipped minimum wage range from 1.2 months to 2.6 months. While the 20 year-old servers gain around 1.5 months of job tenure due to the higher tipped wage, the 25 year-old servers gain around 2 months, and the 30 year-old servers center around a 2.5 month gain. These three trends average out to 2 months.

Secondly, we must consider the "median" server in my data: female, single, near 26 years old, in a county where unemployment is 4%, living in a city with 81,238 people, and receiving about 18% for an average tip. If one looks at the rows most closely associated with these characteristics (rows 9 and 10), the difference between this server in a state where the tipped minimum wage is less than $3 versus one in a state where the tipped minimum wage is greater than $3 is 2.1 months; the former being on the job for 17.9 months and the latter being on the job for 20 months). Therefore, for many servers in my data, the higher tipped minimum wage will increase their months on the job by around 2 months, so 2 months is a good single-number estimate for the increased wage effect. Additionally, it should be mentioned that the type of server most representative of my median server across variables (row 9: 17.9 months) has roughly 1.5 years of job tenure, which is close to the national 2006 median server job tenure of 1.4 years (United States Bureau of Labor Statistics 2016: 10). Therefore, these predicted values likely reflect reality for many servers in 2006.

Aside from the effect tipped minimum wage variable, other prominent effects exist as a result of other variables:

Table 15. Increase in Months on Job for Servers in Higher Tipped Minimum Wage States by Age and City Size

Age	Small Town	Big City
20	1.8	1.2
25	2.2	1.5
30	2.6	1.8
35	3.3	2.2

The previous table shows how the effect of working in a higher tipped minimum state increases with the age of servers. The older the server, the larger the gain in months employed for a tipped wage higher than \$3. In a small town, for a 20 year old, the average gain is 1.8 months; for a 35 year old in the same town, the average gain is 3.3 months. In a large city, for a 20 year old, the average gain is 1.2 months; for a 35 year old it is 2.2 months. Additionally, the model shows that servers in the largest cities have fewer months on the job than servers in other cities, but also that working in a state with a higher tipped minimum wage still increases tenure in those large cities. Therefore, older servers in small towns will see the greatest rise in months on the job for living in a state with a tipped minimum wage of over \$3. However, all servers' months on the job benefit from a higher tipped minimum wage.

Additionally, the effects of the average tip percent received merit a table parallel to the one above. As tips often contribute greatly to a servers' financial stability due to low base tipped wages, it is critical to look at tips' effect on server job tenure as well. I replicate the table above while replacing my key variable—the tipped minimum wage—with the average tip percent variable at different values of 15% and 19%. These are the 25th and 75th quartile markers for average tip percent received in my sample. In the previous predicted values table, I used the median of 18% average tip as a constant. The table below will instead use the median for my tipped minimum wage variable (less than \$3 tipped minimum wage) while showing the increase in months on the job for those with average tip values of 19% compared to 15%:

Table 16. Predicted Months on the Job Focusing on Tips and Using Duan's Smearing Factor

Age	City Size	Average Tip	Unadjusted Months on Job	Adjusted Months on Job (Duan's)	# Months 19% Average Tip Adds Compared to 15% (Duan's)
20	< 25k	15%	8.9	14.2	
20	< 25k	19%	9.9	15.8	**1.6**
20	25k to 100k	15%	8.4	13.4	
20	25k to 100k	19%	9.4	14.9	**1.5**
20	2.5m to 9m	15%	6.1	9.7	
20	2.5m to 9m	19%	6.8	10.8	**1.1**
25	< 25k	15%	11	17.5	
25	< 25k	19%	12.2	19.5	**2**
25	25k to 100k	15%	10.4	16.5	
25	25k to 100k	19%	11.5	18.4	**1.9**
25	2.5m to 9m	15%	7.5	12	
25	2.5m to 9m	19%	8.4	13.3	**1.3**
30	< 25k	15%	13.6	21.6	
30	< 25k	19%	15.1	24.1	**2.5**
30	25k to 100k	15%	12.8	20.4	
30	25k to 100k	19%	14.2	22.7	**2.3**
30	2.5m to 9m	15%	9.3	14.8	
30	2.5m to 9m	19%	10.3	16.5	**1.7**

35	< 25k	15%	16.7	26.7	
35	< 25k	19%	18.6	29.8	**3.1**
35	25k to 100k	15%	15.8	25.2	
35	25k to 100k	19%	17.6	28	**2.8**
35	2.5m to 9m	15%	11.4	18.2	
35	2.5m to 9m	19%	12.7	20.3	**2.1**

Similar to a higher tipped minimum wage, a higher average tip percentage meaningfully and positively impacts a servers' number of months on the job. Overall, servers receiving a 19% average tip had an additional 1.1 to 3.1 months on the job compared to servers receiving an average tip of 15%. In most cases, the higher average tip percentage caused an increase of servers' months on the job of a little under 2 months. As I mentioned in the previous predicted values table analysis, this 2 months estimation comes from two things. Once again, the majority of servers in this data are under 30 years of age; 50% of servers in this data are at or under 27 years old while 75% are under 35 years old. Therefore, one can obtain a good overall picture of months added by a higher average tip percentage by observing the rows corresponding with those 30 and under, as this is where the majority of cases in the data exist on the age spectrum. And among those servers 30 years old and younger, months on the job added by a higher tipped minimum wage range from 1.1 months to 2.5 months. While the 20 year-old servers gain 1.5 months of job tenure or less due to the higher tipped wage, the 25 year-old servers gain around 2 months or less, and the 30 year-old servers gain a little less than 2.5 months. These three trends average out to an amount slightly below 2 months.

Secondly, we must again consider the "median" server in my data: female, single, near 26 years old, in a county where unemployment is 4%, living in a state with a tipped minimum wage of less than $3 and in a city with 81,238 people. If one looks at the rows most closely associated with these characteristics (rows 9 and 10), the difference between this server earning an average tip of 19% versus 15% is 1.9 months; the former being on the job for 16.5 months and the latter being on the job for 18.4 months). Therefore, for many servers in my data, a higher average tip percent received will increase their months on the job by a little under 2 months.

The increase in servers' months on the job is thus very similar between both variables which directly impact servers' earnings. Therefore, a server who begins earning a tipped minimum wage of greater than $3 as compared to less than $3 will gain a approximately the same increase to their months on the job as compared to a server who begins receiving an average tip of 19% compared to 15%. Averaging all the gains in server months for both variables reveals similar positive effects. The higher tipped minimum wage has an average increase of 2.16 months on the job for servers whereas the higher average tip percentage has an average increase of 1.99 months on the job. It should be noted that in the first predicted values table, I controlled for the average tip percent received at its median level of 18% (I used the median values of all variables when they were constants in the table). This average tip of 18% was very close to the second table's focus on the effect of the higher average tip of 19% as compared to 15%.

Therefore, the first table which sought to reveal the positive effect of an increased tipped minimum wage on server job tenure benefitted from the high constant average tip of 18% which was the median. In comparison, when I constructed the second table in order to see the increase in server job tenure due to the higher average tip of 19% compared to 15%, I set my tipped minimum wage dual-category variable at its median level (the mode, in this case) of a server living in a state where the tipped minimum wage was less than $3. Because of this, I did not add any coefficient for the tipped minimum wage when calculating predicted values for the average tip percent table. Exponentiating a higher sum leads to a higher number, so the slightly higher increase in server job tenure partially due to a higher tipped minimum wage (which benefitted from a high constant of 18% average tips) as compared to a higher average tip percentage is negligible. In other words, the positive effects are very much the same; in many cases, both higher-earning conditions result in around a 2-month increase in servers' months on the job.

Analysis of Residuals/Assumptions

As mentioned earlier, the residuals for my non-logged dependent variable model violated the assumption of homoscedasticity (constant variance), but the model with the log-transformed dependent variable fixed this issue. Additionally, no violation of linearity seems to exist.

Chart 5. Scatterplot of Residuals for Non-Logged Model

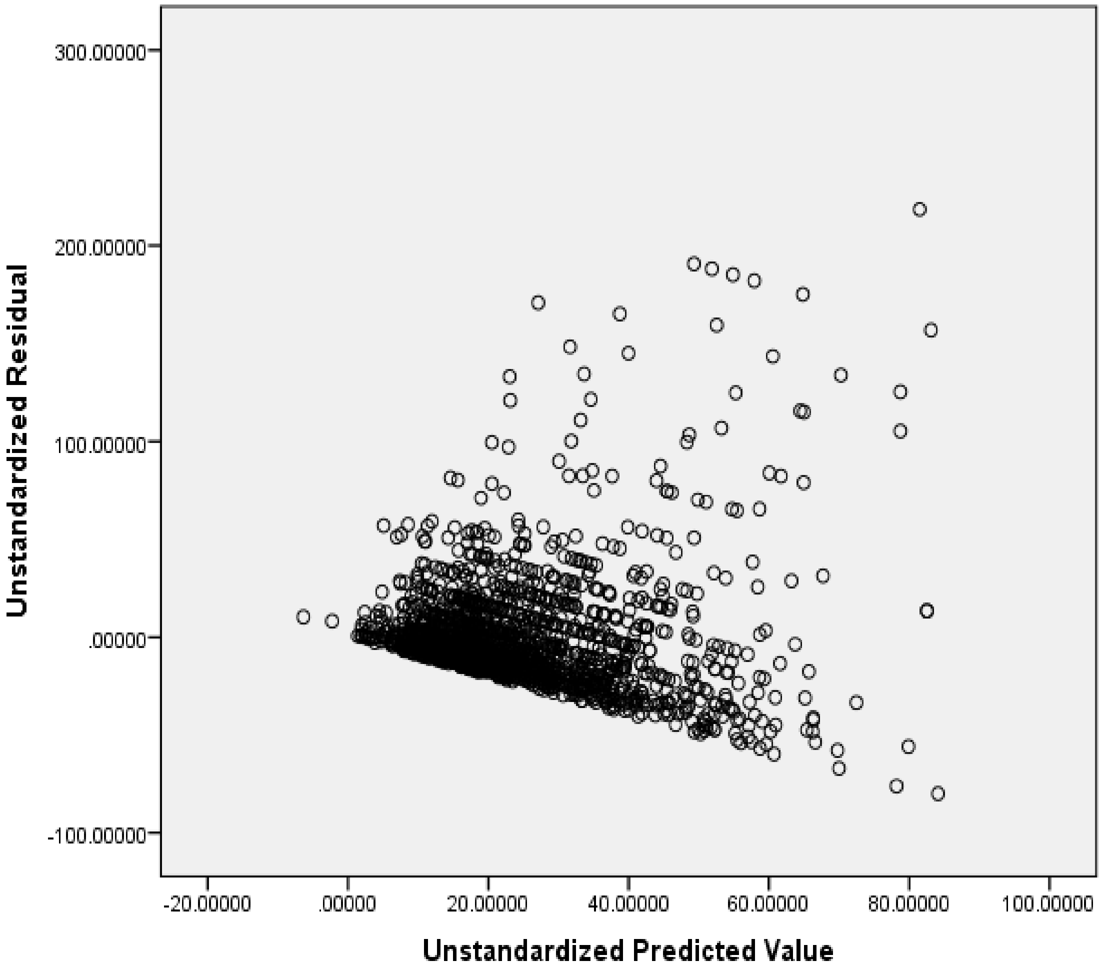
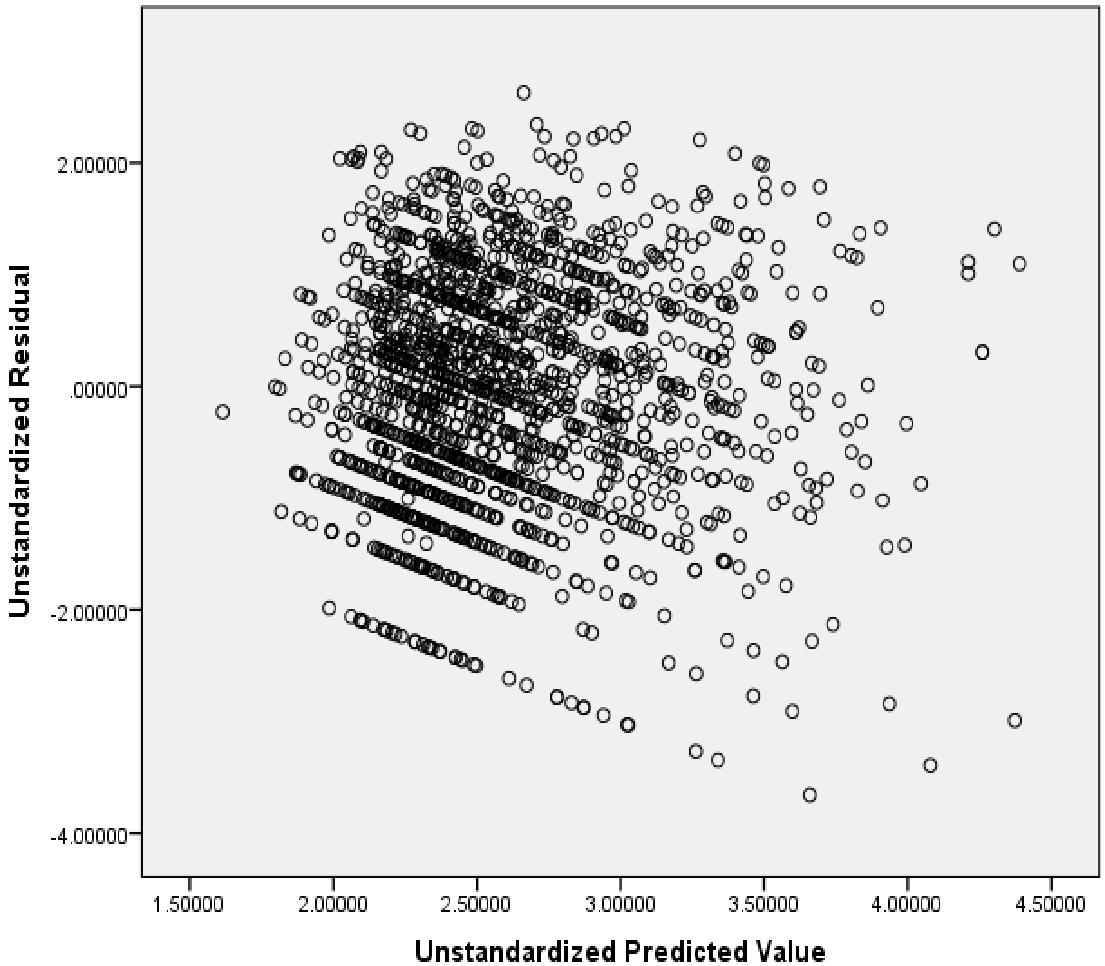
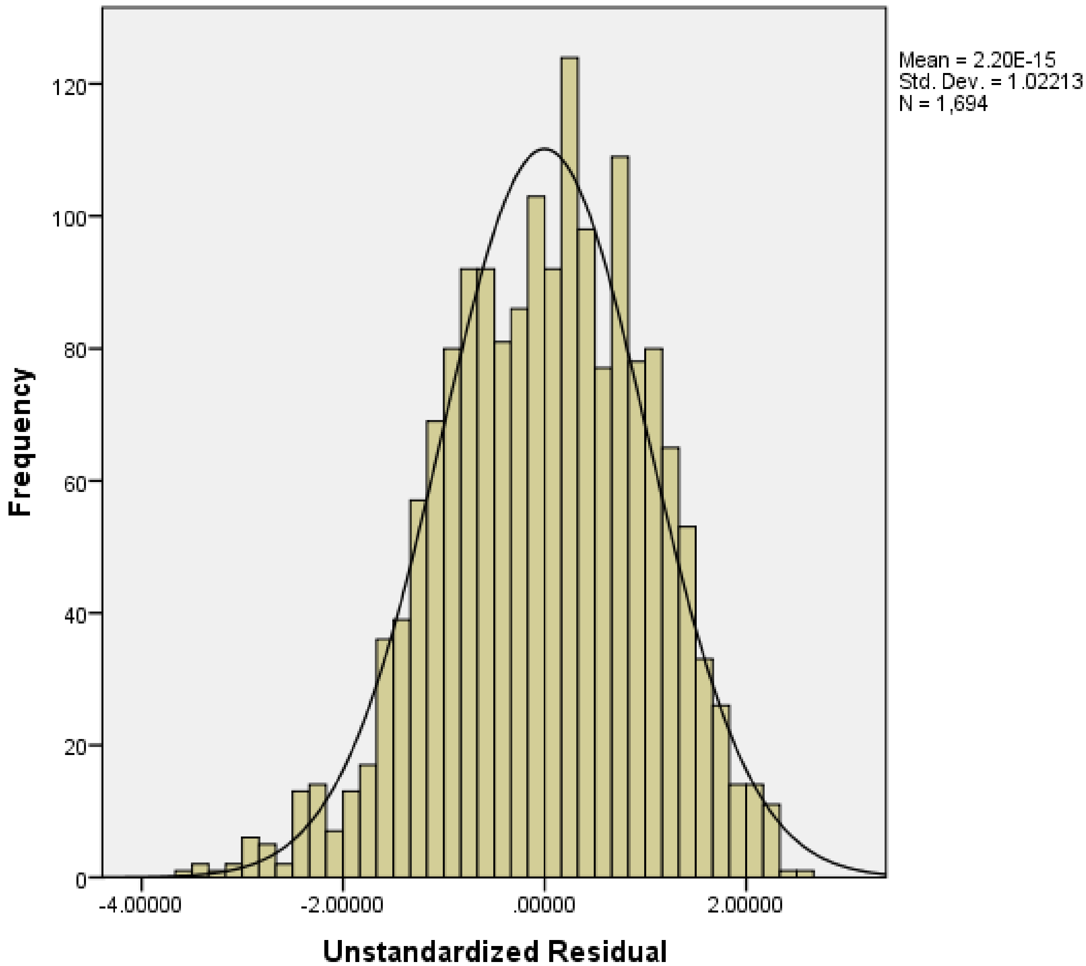


Chart 6. Scatterplot of Residuals for Logged (LN) Model



Additionally, the residuals of my model are normally distributed. As one can see, the distribution largely reflects the imposed normal curve:

Chart 7. Histogram of Residuals with Imposed Normal Curve



Next comes multicollinearity. Multicollinearity does not seem to exist in my data, based on the fact that all tolerance values from my model are well above .10 and no VIF (variance inflation factor) values exceed 10. Therefore, this model does not commit the violation of multicollinearity.

Table 17. Checking for Multicollinearity

Variable	Tolerance	VIF
Age	.803	1.246
Sex	.982	1.019
Married	.832	1.201
County Unemployment	.923	1.083
City Population 25k to 100k	.652	1.533
City Population 100k to 500k	.672	1.489
City Population 500k to 1m	.740	1.351
City Population 1m to 2.5m	.869	1.150
City Population 2.5m to 9m	.825	1.212
Average Percent Tip	.977	1.023
Tipped Min. Wage < $3 vs. > $3	.852	1.173

This data is not completely without fault. Due to the nature of the data—convenience data collected by a hospitality industry researcher who was primarily interested in restaurant server practices that increase tips—there are a couple absent variables that would have been desirable to have in my model. First, according to Batt, Lee, and Lakhani (2014), although hourly wages and tips contribute most to server job tenure, work hours and promotion opportunities also are significant (Batt, Lee, and Lakhani 2014: 19). Secondly, my data did not have an education variable. This is not ideal, as Boles et al. (1995) find that servers with higher levels of education exhibit higher rates of turning over (Boles et al. 1995: 23).

Third, due to only having geographical data and not actual wage earnings of servers in my sample, my model examines the tipped *minimum* wage's effect on servers' job tenure levels. Servers do receive promotions and pay increases, and my tipped wage variable does not account for that. However, this may not be a significant problem, as only two-thirds of servers surveyed nationally reported being offered promotions with pay increases (ROC United 2011, in Jayaraman 2016: 14). Finally, the study would have benefitted from a "flat tips received" variable as opposed to one based on percentages.

Conclusion

In sum, restaurant serving is precarious work in many ways. Due to server reliance on customer tips—as well as the not-so-perfect relationship with good service and higher tips—the job is financially precarious. Restaurant servers must also deal with notoriously unreliable hours, a lack of benefits, and high rates of sexual harassment. It is little wonder that restaurant servers have one of the highest voluntary turnover rates among all types of work (Bureau of Labor Statistics 2016: 29). Academic literature on low wages suggests that higher minimum wages reduce turnover and increase job tenure in many occupations.

Indeed, this study reinforces the idea that higher tipped minimum wages for restaurant servers increase their overall tenure levels. The tipped minimum wage variable was statistically significant ($p = .05$). As for the size of the coefficient, after applying Duan's (1983) Smearing Estimate, it seems that in many cases in my data, a server living in a state in 2006 with a tipped minimum of greater than $3 would have around 2 months longer job tenure than a server living in a state with a tipped minimum wage of less than $3. This 2 months average approximation would be a bit higher or lower given differing variations of characteristics of servers based on variables in my model (e.g., gender, age, city size, average tip percent, etc.). As the sample of white servers in 2006 was generally representative of the wider white server population, the significant p-value and sizable coefficient considered together indicate that a positive relationship between higher tipped minimum wages and longer server job tenures likely exists. Significant relationships with job tenure also exist for server age, if a server lives in a very large city of 2.5 million to 9 million people, and for average tip percentages received. It should be noted that the effect of higher average tip percentages is approximately the same as that of higher tipped wages; both lead to a 2-month increase in server job tenure on average. This is likely because both higher base pay and higher tips contribute to a server's financial well-being which in turn positively impacts a server's tendency to stay at his/her place of work for longer.

Based on this study and others, it could very well be argued that increases in tipped wages would be beneficial not only to the servers, but also to restaurants which invest large amounts of money into hiring and training new servers. As Liu et al. (2016)—in their study on youth labor markets using U.S. county-level panel data from 2000 to 2009—write, "Reduced turnover would be a positive outcome for many employers of minimum wage workers who are forced to deal with very high turnover rates" (Liu et al. 2016: 38). Therefore a tipped wage increase could be good for both management and workers. Additionally, researchers Hirsch et al. (2011), examining minimum-wage laws of 2007 to 2009 and their effects on quick-service restaurants in Alabama and Georgia, find that outside of low-volume restaurants, minimum wage increases—in good economic times—neither necessitate increased prices nor fairly diminished profits (Hirsch et al. 2011: 33). In fact, higher wages may in-part present an "opportunity for increasing business profits" (Harris 2010: 117). Researchers Batt, Lee, and Lakhani (2014) show that turnover costs are immense: $18,200 for a restaurant with 30 employees, $182,000 for a chain of 10 restaurants, and $1.82 million for a chain of 100 restaurants (Batt, Lee, and Lakhani 2014: 2). They assert that higher wages are one key factor in reducing employee turnover. In conjunction with greater job security, longer hours, more discretion at work, and greater rates of promotion, higher tipped and non-tipped wages in restaurants "can reduce employee turnover almost by half" (Batt, Lee, and Lakhani 2014: 1).

As profits do not necessarily suffer with higher wages in the restaurant industry, it is unsurprising that several different studies have shown that minimum wage increases also do not necessitate layoffs (Hirsch et al. 2011: 32; Dube et al. 2010: 962; Dube et al. 2013: 2). Hirsch et al. (2011) not only find no/little need to cut employment levels, but they also find this to be true for employee hours. They write, "We find, in line with other recent studies, that the measured employment impact is variable across establishments, but overall not statistically distinguishable from zero. The same absence of a significant negative effect is found for employee hours, even when examined over a three-year period" (Hirsch et al. 2011: 32). Additionally, McDonald's CEO Steve Easterbrook has recently stated that the company's lower turnover, increased sales and customer satisfaction could be attributed to McDonald's recent wage increases and expansion of employee benefits (Mierjeski 2016).

Therefore, mounting evidence suggests that most restaurants could—in the context of increased state tipped (and non-tipped) minimum wages—maintain most profits, employment levels, and employee hours, all while providing servers with more than just precarious subsistence wages. And much academic literature suggests that reducing employee turnover—a largely agreed-on consequence of increasing wages—saves business owners significant money. Mandating increased tipped wages in America is thus not only morally correct, but also advantageous to restaurant owners in reducing their frequency of searching for and hiring new servers. The costs saved by reducing turnover seem to largely balance those incurred by increasing tipped wages and lifting many servers out of poverty. This study reinforces the idea that increasing tipped minimum wages for restaurant servers increases their levels of job tenure. Considering my results in conjunction with aforementioned other studies, higher tipped wages do not seem like such a tall order; it is high time higher tipped wages receive a seat at the social policy discussion table.

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Vita

John Sienkiewicz graduated *summa cum laude* from North Central College with a BA in sociology. There he conducted an independent study on American popular music's lack of economic critique in both times of economic strife—the 1960s—as well as times more economically-stable—the 2000s. Sienkiewicz found that American popular music has been "colonized" by the music industry, making for popular music overwhelmingly devoid of important messages such as those criticizing the financial difficulties Americans face in a troubled economy. Sienkiewicz also assisted Dr. Louis Corsino in his study on Italian-American organized crime in Chicago Heights during the 20th century. With Sienkiewicz's research assistance, Corsino determined that Italian organized crime in Chicago heights acted as a means to overcome diminished social mobility due to anti-Italian discrimination. In the spring of 2014, Sienkiewicz received the Outstanding Major in Sociology and Anthropology Award from North Central College. Sienkiewicz is receiving his MA in sociology from Loyola University Chicago in December 2016, once again *summa cum laude*. Sienkiewicz's areas of research interest include—but are not limited to—urban sociology, labor, and social policy.